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A Summary of Sociological Concepts Related to Social Network and Its Techniques for Quantifying Social Cohesion, Social Position, Social Distance

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Abstract

This is a summary of Sociological Concepts Related to Social Network and Its Techniques for Quantifying Social Cohesion, Social Position, Social Distance. Hopefully, they will be useful for designing search algorithms in more sociological sense.

1 Background

We are moving rapidly from a society built around relationships in homes, neighborhoods, workplaces, places of worship, and voluntary organizations, to a globally connected society with interactions that span large spatial and social distances. Sociological understanding of this transformation has yet to be achieved. This transition can be thought of as a transition from strong to weak ties. Humans form direct communities online, in the context of social networking sites, email communications, and virtual worlds, etc. They also, however, form indirect communities via the development of shared tastes, consumption patterns, media access, etc. Understanding the character and consequences of these direct and indirect relationships has been a key focus of business such as Google, Amazon, Pandora, and Yahoo, but has been relatively under-examined by contemporary computational social science.

In the spring of 2011, access to social networking sites was largely hailed as a prime facilitator of individuals across North Africa and the Middle East as they organized expressions of social unrest and political discontent on a massive scale and then communicated the results of those organized expressions with lightening speed. On the civilian side, the marketing community is keenly interested in exploiting sociological links, especially the weak sociological links that have recently become emplaced in and accessible through the Internet. Worldwide, internet usage is increasing at an astounding rate, particularly the use of social networking sites. The number of adult internet users in the United States doubled between 2008 and 2010 (Hampton, Goulet, Rainie Purcell 2011[19]). A recent Pew Research Center survey (reported that in the United States, social networking site use has risen from 26% of all adults in 2008 to 47% in 2010 (Rainie, Purcell, Smith 2011[31]). Most of these users (92%) are on Facebook; 13% use Twitter (Rainie, Purcell, Smith 2011). Evidence from this report suggests that the movement from organizationally and geographically organized communities to online communities has augmented rather than supplanted other types of sociality. Internet users are even more likely than the average American to belong to voluntary groups or organizations (80% versus 56%). Social networking site users are even more likely than other internet users to belong to organized groups, with Twitter users being the most likely to belong to voluntary groups or organizations. Facebook users are also more politically engaged than other U.S. adults (Hampton, Goulet, Rainie Purcell 2011). So, while mediated interactions are taking place at unprecedented rates, they do not seem to be supplanting other, more conventional forms of social organization. Rather, it is likely that these types of relations interact with one another in ways that are not yet adequately understood.

2 Useful Sociological Concepts

2.1 Tie Strength and System Size

Social network techniques for analyzing structure and position within social systems largely developed to understand strong sociological links (families, hierarchical/command organizations, communities with specific structure, nation states, etc.). These techniques were later applied to the study of weak social ties (acquaintances, occasional encounters, etc.), but there has been relatively little comparison of the differences between the two types of social systems. Strong sociological links are responsible for important aspects of human society, including but not limited to the ability to build entities that allow for coordinated action of large numbers of people. Strong sociological links involve loyalty and giving/accepting orders due to monetary and religious relationships. Weak sociological links, on the other hand, are the most common sources of new information which are now increasingly available to collect via internet. Both strong and weak links play positive roles in human society and in human progress. However, with the Internet and many other networking capabilities, the balance between strong and weak links is changing. As the accessibility of all links increases, the relative importance of the weak links is increasing.

Tie strength is a property of relationships, and generally refers to the intensity of commitment, constraint, or emotion attached to a particular link. Another way to characterize the difference between conventional social environments and those in the world of Web 2.0 is in terms of system size and complexity. While not equivalent, these are somewhat conflated in the scholarly literature. So, when we talk about research on weak versus strong ties, we primarily are distinguishing between analysis of the relational structure of small, often bounded groups, versus analysis of large, complex social systems.

An advantage of studying small, bounded groups is the ability to work with whole networks. Many of the approaches to looking at social structure and social position in the social network literature rely on graph theory and utilize the entire matrix of relations in their computation (Carrington, Scott, and Wasserman 2005). Much of the focus in the contemporary social network environment is on very large scale, sparse, and complex social systems. It remains an open question whether social network measurement approaches developed to understand small whole networks are optimal for understanding larger, sparser, more complex communication networks or knowledge networks based on weak links. In fact, some recent research suggests that other dynamics whose properties we thought we understood in simpler networks may operate differently in more complex systems. In light of this, we will survey the social network literature regarding the measurement and quantification of various indicators of social capital including social cohesion, social position, and social distance and consider to their potential applicability to large complex systems of weak relations.

2.2 Social Cohesion

Social cohesion has long been a subject of investigation in the study of groups (Albert 1953, Cartwright 1968, Lott 1961, Van Bergen and Koekebakker 1959). Social cohesion refers to the degree of solidarity within a group or social system and usually is defined as the degree of attraction and/or commitment toward the group/system held by individual members of the group/system. This premise of an individual-to-group relation has been the subject of some debate (can individuals actually relate to groups or do they only relate to other individuals?). The literature largely supports the idea that individuals can, indeed, have relationships with abstract groups and that these relationships can precede and supercede relations between individuals within those groups (for a review, see Friedkin 2004[**?**]).

Social network researchers also have used a variety of structural properties of the group to characterize its cohesion, rather than relying on individual reports of attraction or commitment to the group. These include the extent of positive ties within the group (Cartwright 1968[**?**]), the degree of symmetry among positive ties within the group (Moreno and Jennings 1937[**?**]), and the density of interpersonal relations (Festinger et al. 1950[**?**]). There are also numerous ways of identifying cohesive subgroups within larger systems (Wasserman and Faust 1994). These approaches, however, fail to capture the individual-to-group aspect of social cohesion, and run the risk of creating a tautology if we want to use structural features to predict social cohesion. Research using more classic measures of social cohesion reflecting individual commitment to the group finds that even groups that are large, complexly differentiated, sparse, and composed of weak ties can be highly cohesive when they have conducive structures (Doreian and Fararo 1998). These include reachability (Markovsky 1998[24]) and a low density of negative or punishing ties (Friedkin 2003[**?**]).

Additional research suggests that it rather the repeated activation of positive ties that produces group cohesion (Lawler, Thye and Yoon 2000; McPherson and Smith-Lovin 2002), rather than simply the quantity of them. This finding that ongoing nature of social relations differentiates them from other kinds of ties considered in isolation is related to the embeddedness approach in economic sociology (e.g., Granovetter 1985; Uzzi 1999). Embeddedness takes into account the degree to which mutual ties, reachability, and other opportunities for feedback loops in a network system create additional pressures toward trust and cohesion. When a relationship is embedded within a larger system of relationships, there is both a larger shadow of the past and a larger shadow of the future. This has the effect of creating more enduring relationships and a greater commitment to the groups or systems in which these relationships are embedded.

In summary, social cohesion is understood as a way of characterizing the stability and intensity of the relationship between individual members of a group or system and the group itself. Structural position (reviewed further below) and embeddedness predict the individual-to-group relationships from which group level cohesion derives. Structural conditions like density, reachability, reciprocity, and repetition of tie activation predict cohesion at the group level. While nodal reach and system reachability are not easily calculated in large or incomplete systems, reciprocity and repetition of tie activation are network features that can be accessed with egocentric data from sampled nodes, and so are features that might easily be used in understanding the dynamics of massive, complex systems.

2.3 Various Measures of Centrality

The mostly widely investigated social network measures are those characterizing social position sometimes called social prominence or network centrality. In the social network literature, there are four primary means of characterizing the structural position of a particular node degree, betweenness, closeness, and Bonacich power. These are methods of determining the centrality of a vertex within a graph. In the context of social networks, they are typically used to determine the importance of a particular person within the group or system. The usefulness of each of these methods of characterizing structural position depends on features of the system, the social context, and the nature of the resource flowing through the graph or network. We will describe these further below.

Degree. The simplest and among the most frequently used measure of structural position is degree based centrality. In symmetric networks, this is simply the number of lines or edges connecting a particular node or vertex to other nodes (Freeman 1979[16]). In simple affiliation systems, this is considered to be a basic characterization of popularity. A count of ones Facebook friends is a fairly ubiquitous contemporary measure of degree centrality among contemporary college students. While Facebook friendships occur in a symmetric social network, many naturally occurring networks are fundamentally asymmetric in nature. Liking, respect, information seeking, and assistance are routinely exchanged asymmetrically. In these cases, it helps to distinguish between in-degree (number of ties received) versus out-degree (number of ties sent) to determine social prominence in a network. In-degree is a more precise measure of prominence when the resource flow is positive and or deferent (e.g., respect, advice-seeking). Out-degree may be a more precise measure of social prominence when the resource flow is the diffusion of information. Nodes with high out-degree can serve as gatekeepers in a social system. Asymmetry between out-degree and in-degree can also serve as a measure of node prominence. When group size is known, actor degree can be standardized by the group size in order to compare prominence of actors across groups (Wasserman and Faust 1994:179).

An elaboration of this approach developed by Bonacich (1987) uses iterative simultaneous equations to converge on an estimate of power that combines degree of actor with information about the actors relational neighborhood. This method recognizes that being connected to others with many connections can increase an actors importance in a positively connected (contagious) network and simultaneously decrease ones power in a negatively connected (competitive) network. Imagine a network in which Sally and Bob each have five friends. Sallys friends each have a high number of other friends; Bobs friends are isolates and are not friends with many others. If the social process of interest is contagious, like the diffusion of information, the transfer of disease, or even diffusion of positive regard, then Sally would have more influence than Bob. She gets her power by being connected to other highly connected others. In contrast, if the resource flowing across the network is competitive, then Bob may gain more power by being connected to others who are more dependent upon him for the competitive resource. Bonacichs algorithm accordingly allows for specifying the level and direction of attenuation in the network.

Closeness. A different approach to quantifying an actor's power in a social network is closeness-based centrality (Freeman 1979[16]). This approach presumes that a node's power is a function of it geodesics. The simplest version is simply an inverse of the sum of all distances from an actor to all other actors in a network. This approach to power is especially useful in positively connected (contagious) networks across which resources diffuse with some moderate rate of decay. An elaboration of the closeness centrality approach, called reach centrality, considers what portion of the network an actor can reach with each additional number of steps (Hanneman and Riddle 2005[20]).

Betweenness. A third general approach to quantifying an actor's power in a social network relies on betweenness-based centrality (Freeman 1977[15]). This approach recognizes that nteractions between unconnected members of a network often critically depend on other actors in the system - especially those who lie on the paths between the two. The simplest measure of betweenness centrality simply counts all of the geodesics between all pairs of actors in a system which contain a particular actor. An elaboration of this idea, called information centrality, generalizes this to include all paths between all actors, weighted by the inverse of their lengths when calculating centrality (Stephenson and Zelen 1989[37]). This takes into account the idea that information does not always flow along the shortest path, and that actor can gain importance by controlling the flow across many paths, as well as by controlling only a few short paths.

Eigenvector Centrality. A fourth approach to quantifying structural position uses a factor analytic procedure to discount closeness to small local subnetworks (Bonacich 1972[2]). This approach, called eigenvector centrality, allows researchers to differentiate between proximity in the global structure and proximity in more local substructures, by computing principal components of the actor distance measures and generating an eigenvalue for each actor on each structural dimension (Freeman 1979). This approach generates estimates of structural position that are very close to degree based centrality when there is a fairly flat distribution of degree, or in core-periphery structures, where high degree nodes are connected primarily to other high degree nodes (Bonacich 2007[**?**]). But, in structures with many connections between low degree and high degree nodes, the kinds of hierarchical lustering that characterizes most naturally occurring systems (Barabasi et al. 1999; Watts et al. 2002; Watts 2004 [39]) this method produces distinctively different and much more useful predictions.

Dependence-based power. Markovsky and colleagues (Markovsky et al. 1994; 1998 [23] and [24]) have developed another set of measures specifically designed to measure potential for structural influence in negatively connected, or competitive networks. The simplest form of such competition is when there is no resource flow (perfect decay) and nodes are limited to single exchange partners. In such networks, the structure of relationships in one part of system can constrain power relations within dyads far away in the system in systematic ways. The simplest of these graph-theoretic power indices (called GPI) subtracts the number of disadvantageous paths (the number of unique even length paths between a node an all other nodes in the system) from the advantageous paths (the number of unique odd length paths between a node and all other nodes) to generate a measure of dependence-based power. Individuals with many ties to individuals with no other ties (paths of length 1) are rewarded for their ties to dependent others. These measures have been used to successfully predict power use and exchange outcomes in a number of experimental studies of human interaction.

These measures of structural position have varying utility by context. In whole networks we can easily see how the decay rate of a resource flow determines which measure of structural position is most useful. When a resource flow is very quickly consumed, then degree based centrality may be the most useful. We can think of many social behaviors and affects that are like this. If Sally smiles at Bob, her smile is consumed. Bob can smile at another co-worker but it wont be Sallys smile. In this case, we want to understand patterns of single-transfer social behaviors and affects, degree based centrality may be sufficient. When a resource flow can travel through one or more nodes, but with some decay factor, closeness-based centrality becomes more important. Information flows across a network, but tends to lose veracity and sometimes change (increase or decrease) intensity with each transfer. Consequently, being closer to the source provides one with more accurate information. Being connected to many well-connected others may facilitate more influence than simply having the most friends. When individuals serve as liaisons across various densely connected regions in a system, they accrue betweenness-based power, allowing them to serve as gatekeepers for resources that have slower decay functions.

Closeness-based centrality, betweenness-based centrality, and dependence-based require whole networks for computation. This limits their utility to contexts where full information is available and raises the question their computational efficiency when applied to very large, sparse networks. Degree based centrality has the benefit of being easy to access and not requiring whole network information and so can easily be used in the context of egocentric data or in large, complex, and sparse networks. Some of the variants of degree based centrality, including eigenvector centrality and the variant, PageRank, used by Googles search engine, can be calculated with only the use of first-order ties, making them computationally much more efficient in large, sparse, and incomplete networks. With the consideration one additional order of relationships (out to 2nd order ties), the formula could be substantially improved to take into account the kind of local-distal effects better captured by whole-network approaches such as closeness, betweenness, and especially dependence-based power.

2.4 Social Distance

Social distance measures have been used in sociology for nearly a century. Many of these measures, like the classic Bogardus social distance scale (1925), are self-report attitudinal measures. There also is a long history, however, of quantifying social distance and social positions using social network techniques. Most of these techniques for identifying social distance at the dyadic level are the same as those used to identify social cohesion at the group or system level. The simplest of these techniques require that the geodesic distances between the nodes in a network or subnetwork be small. Others compare within-group ties to out-group ties. Other approaches make use of clustering or multi-dimensional scaling techniques to represent social distance along a small number of dimensions for visual interpretation.

Some of these techniques focus on identifying sets of structurally equivalent actors. One such approach uses Pearsons correlation as a measure of structural equivalence and uses the convergence of iterated correlations between relations as a means of partitioning into subsets. Using connection through music tastes as an example let us describe this classic technique (Breiger et al. 1975, White et al. 1976). Take an adjacency matrix A of actors and music purchases. Multiply the matrix A by its transpose A* to get an actor X actor matrix of people connected through their shared music preferences. Correlate the rows and columns of this new matrix. Replace the values in the matrix with the results. Repeat until the cells are filled with 1s and 0s. Separate the 1's and 0's into separate matrices. Replace with values from original Actor by Actor matrix and start again. Each successive split will group actors into subgroups with more similarly shared patterns of relations to others (through shared music preferences). This creates a binary tree of partitions among actors, with all actors being partitioned into exhaustive and mutually exclusive subsets. Finally, partition the original actors by the resulting positions and permute the matrix to reveal the relationships between the structurally equivalent blocks.

A variant on this technique relies instead on the Euclidean distances between the ties to and from two actors, instead of using Pearsons correlations to capture degree of similarity (Burt 1976). For each pair of actors i and j take the Euclidean distance between rows i and j and columns i and j. When two actors are structurally equivalent (connected to the same other actors), they distance between them will be 0. Once a matrix of equivalence relations has been computed, actors can be partitioned into cohesive subgroups through the use of hierarchical clustering.

The correlation based measure of structural equivalence has the advantage of capturing the equivalence of actors who have similar kinds of relations with similar kinds of others, while the Euclidean distance measures

For example "long ties" (those connecting actors who are socially distant along other social dimensions) increase diffusion rates in some classic studies, like Granovetter's (1974) study of job seekers in which individuals were more likely to find jobs via weak (and long) ties than via strong ties. In other words, long ties speed simple contagions. Long ties, however, actually slow diffusion of information when adoption requires multiple affirmations. In these systems, long ties slow complex contagion processes (Centola and Macy 2007; Centola, Eguilez and Macy, 2007).

3 Conclusion

The PI and co-PI have immersed in the mathematical and sociological literatures on social networks and made some initial connections between them. Above, we have briefly summarized the We have summarized the sociology of social structure, position and influence in strong and weak networks. In the appended document, we summarize the mathematical study about the Google search algorithm along with some suggested improvements based on and this sociological literature. To further explore and develop these connections and their implications will require a greater time investment than afforded by this seed project.

With more time, this research team could more deeply digest the existing information, and propose some new algorithms, making use of sociological insights to improve mathematically the characterization of relations in large, complex systems. The PI and co-PI are more than willing to continue our joint work toward a better understanding of the searching algorithms and discovering how to better situate them in the larger contexts of existing mathematical and sociological knowledge.

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